



Technical Report PTR-1092-80-8 Contract No. N00014-80-C-0150 Work Unit No. NR 197-064 August 1980

HOW WELL DO PROBABILITY EXPERTS ASSESS PROBABILITIES?

SARAH LICHTENSTEIN BARUCH FISCHHOFF

DECISION RESEARCH
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Prepared For:

OFFICE OF NAVAL RESEARCH

Department of the Navy 800 North Quincy Street Arlington, Virginia 22217



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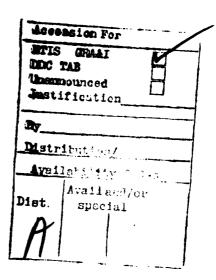
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How well do probability experts assess probabilities?	Technical Report 1/80 -
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Sarah/Lichtenstein Baruch/Fischhoff	(5) N90014-80-C-0150 ~~
9. PERFORMING ORGANIZATION NAME AND ADDRESS Decision Research	10. PROGRAM ELEMENT, PROJECT, AREA & WORK UNIT NUMBERS
A Branch of Perceptronics 1201 Oak Street, Eugene, Oregon 97401	Work Unit NR197-064
11. CONTROLLING OFFICE NAME AND ADDRESS	AUG FRONT DATE
Office of Naval Research	August 280
Arlington, Virginia 22217	13. NUMBER OF PAGES 22
14. MONITORING AGENCY NAME & ADDRESS(II different from Controlling Office)	15. SECURITY CLASS. (of this report)
(15)34	unclassified
16. DISTRIBUTION STATEMENT (of this Report)	15a. DECLASSIFICATION/DOWNGRAM SCHEDULE
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have overcorrected for the overconfidence error: they were notably underconfident, whereas the untrained subjects were overconfident and the trained
subjects were mixed. The experts were more sensitive than the other two
groups to variations in item difficulty. However, even they showed a substantial insensitivity to difficulty, relative to ideal performance. Introspection suggests that this second error would be hard to overcome.

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Subjective assessment of probabilities has in recent years increasingly been recognized as an integral part of decision making, both personal (cf. Jungermann, 1980) and public (e.g., the "Rasmussen Report," U.S. Nuclear Regulatory Commission, 1975). This recognition has led to a burgeoning research literature on people's abilities to make such assessments (see Lichtenstein, Fischhoff & Phillips, 1977). Typically, participants in this research are presented with a series of two-alternative, forced-choice questions. For each question, the assessor first chooses the correct alternative and then assesses the probability that the chosen alternative is in fact correct. Analyses of these data have focused on calibration. An assessor is well calibrated if, over the long run, for all alternatives assigned a given probability, the proportion of true alternatives is equal to the probability assigned. Thus, for example, just 70% of all alternatives assigned a probability of .7 should be correct. When the assessed probabilities are larger than the proportions correct (e.g., 90% confident but only 75% correct), the assessors are called "overconfident." The reverse situation is called "underconfidence."

Two robust findings have emerged from this research. First, people are usually overconfident; they believe they know more than they actually know. Such overconfidence has been demonstrated in a variety of tasks (Fischhoff & Slovic, 1980), response modes (Fischhoff, Slovic & Lichtenstein, 1977), and subject populations (Wright, Phillips, Whalley, Choo, Ng, Tan & Wisuda, 1978; Cambridge & Shreckengost, Note 1).

The second general finding is that the degree of overconfidence is related to the overall difficulty of the task. People are most overconfident with the hardest tasks (Clarke, 1960; Nickerson & McGoldrick,

1965; Pitz, 1974). As task difficulty decreases, so does overconfidence, until, with quite easy tasks, people are underconfident (Lichtenstein & Fischhoff, 1977). Apparently, people are insufficiently sensitive to task difficulty, and fail to shift the distribution of their probabilistic responses as much as they should as task difficulty changes.

Recent attempts to reduce overconfidence by training (Lichtenstein & Fischhoff, 1980) or improved task design (Koriat, Lichtenstein & Fischhoff, 1980) have been moderately successful. However, no one has managed to enhance sensitivity to task difficulty.

All this research has produced a new kind of expertise: people who have studied probability assessors and who are aware of common errors. The present study explores such experts' ability to use their knowledge to overcome the errors exhibited by naive assessors. Their performance is here compared with that of naive subjects and of subjects who had previously been trained to be well calibrated.

Method

Subjects

Experts. The eight expert subjects, five males and three females, included the present authors, two of their research assistants, and four other psychologists who have done research in probability assessment. All reported having read the research literature on calibration and overconfidence.

Trained subjects. In a previous paper (Lichtenstein & Fischhoff, 1980), we reported the results of two studies in which we trained 24 subjects to be well calibrated, using individualized feedback about calibration after each of 3 or 11 sessions of 200-item, general-knowledge tests. Sixteen (8 females and 8 males) of those 24 subjects agreed to

serve in the present experiment. Of these, six had received 11 sessions of previous training, during which they had responded to the 500 items used in the present study, randomly intermixed with 2,500 items covering other topics. However, since subjects had not been told the correct answer to any item during their training, and since a year had elapsed between the end of training and the present experiment, we felt that having previously seen the test items would not significantly affect their present performance. The other ten trained subjects had received only three sessions of training, and thus had been exposed to only a small fraction of the items used here. Three to six months had elapsed between their training and the present experiment.

Untrained subjects. The untrained subjects were 13 people (9 males and 4 females) who responded to a job listing at the University of Oregon branch of the State Employment Division.

Stimuli

The 500 items were of three types. The first 289 items listed pairs of continents, countries, states, or cities; the task was to indicate which was more populous (e.g., [a] Las Vegas, [b] Miami; [a] Helsinki, Finland, [b] Milan, Italy). The next lll items listed a base city followed by two other cities; the task was to indicate which of the two alternative cities was farther in distance from the base city (e.g., Melbourne: [a] Rome, [b] Tokyo). The final 100 items listed two historical events; the task was to indicate which event happened first (e.g., [a] Magna Carta signed, [b] Mohammed born).

The items were selected by our secretaries from almanacs, under general (and vague) instructions not to make the test too hard or too easy and to avoid deceptive items (i.e., those that might be answered incorrectly by most people).

Difficulty. In previous research on the relationship between task difficulty and calibration, difficulty was defined either intuitively (based on subjects' presumed familiarity with the topics; Pitz, 1974), or on the basis of subjects' performance in the experiment (i.e., items for which more subjects chose the correct alternative were taken as easier; Clarke, 1960; Lichtenstein & Fischhoff, 1977). The latter strategy leads to an artifactual inflation of the difference in calibration between easy and hard tests that is difficult to separate from valid effects.

To avoid this artifact, the present experiment was designed to define item difficulty a priori. Each item involved two numbers: two populations, two distances, or two years. We assumed that the more similar these two numbers, the harder the item is likely to be. To get a measure of difficulty, we formed the ratio of the larger number to the smaller number (for the historical events, the ratios were formed from the number of years elapsed since the events occurred). The 250 items with the largest ratios were designated as easy; the rest were called hard. The ratios varied from 1.01 to 78.79; the median, at which the hard/easy division was made, was 1.84.

Instructions. The instructions were brief:

For each question select the answer you believe to be correct (your best guess). Then assess the probability that your answer is, in fact, correct. This probability can be any number from .50 to 1.0. It can be interpreted as your degree of certainty about the correctness of your answer. For example, if you respond that the probability is .6, it means that you believe that there are about 6 chances out of 10 that your answer is correct.

A response of 1.0 means that you are absolutely certain that your answer is correct. A response of .5 means that your answer is as likely to be right as wrong. Since there are two possible answers, if you make a pure guess, you would probably be right about 1/2 of the time—thus, .50 would be an appropriate probability for such guesses. Write your probability in the space provided on the answer sheet.

To repeat, your probability is a measure of your degree of certainty that your chosen alternative is the correct alternative. It is a number from .50 to 1.0, where .50 means complete uncertainty and 1.0 means complete certainty.

In addition, the expert and trained subjects (all of whom knew about calibration) were asked to be as well calibrated as possible.

All subjects were run individually. The trained and expert subjects who did not live in Eugene were contacted by mail. The trained and untrained subjects were paid for their participation; the experts were not.

Results

Two subjects, one untrained and one trained, apparently misunderstood the instructions for the middle section of the test; instead of picking the city <u>farthest</u> from the base city, they seemed to have picked the <u>closest</u> city. For those 111 items, the untrained subject selected the correct alternative only 36% of the time and the trained subject only 8% of the time. Furthermore, they erred most often on the easiest items. These subjects were dropped from the study. The results that follow are thus based on 8 expert, 15 trained, and 12 untrained subjects.

Performance measures

Table 1 shows the mean and range for several measures of subjects' performance. The experts were most knowledgeable, correctly identifying an average of 75% of the right answers, but they were not the most confident.

Overconfidence. A measure of overall overconfidence is the signed difference between the mean assessed probability and the proportion of correct alternatives chosen. A positive sign indicates overconfidence; a negative sign, underconfidence. By this measure, the untrained group was predominantly overconfident; only one of the 12 subjects was underconfident. Similar overconfidence has been found in previous studies with untrained subjects (Lichtenstein et al., 1977). In contrast, the experts were all underconfident. The trained group was more varied: five were overconfident and ten were underconfident. Figure 1 shows the calibration for the three groups; the overconfidence of the untrained group (represented by a curve falling below the diagonal) and the underconfidence of the experts are readily apparent.

Calibration. A measure of calibration proposed by Murphy (1972, 1973) and used in our previous work (Lichtenstein & Fischhoff, 1977; in press) is the mean squared difference between the assessed probabilities and the corresponding proportions of correct answers, weighted by the number of responses at each point. It measures the mean squared vertical distance, in a plot like Figure 1, between the points and the diagonal. The calibration scores appear in the last row of Table 1. The expert and untrained groups were indistinguishable ($\underline{t} = .61$; $\underline{p} > .5$), whereas the trained group was significantly better than both the others ($\underline{t} = 2.44$; $\underline{p} = .02$).

Table 1
Means (and Ranges) of Performance Measures

for all 500 Items -

	Group			
Measure	Untrained	Trained	Experts	
Proportion Correct	.684	.667	.750	
	(.630 to .837)	(.574 to .786)	(.676 to .806)	
Mean Response	.741	.648	.682	
	(.664 to .837)	(.559 to .764)	(.629 to .729)	
Overconfidence	+.057	029	068	
	(008 to +.165)	(121 to +.046)	(123 to004)	
Calibration	.0118	.0055	.0100	
	(.0013 to .0339)	(.0009 to .0176)	(.0008 to .0172)	

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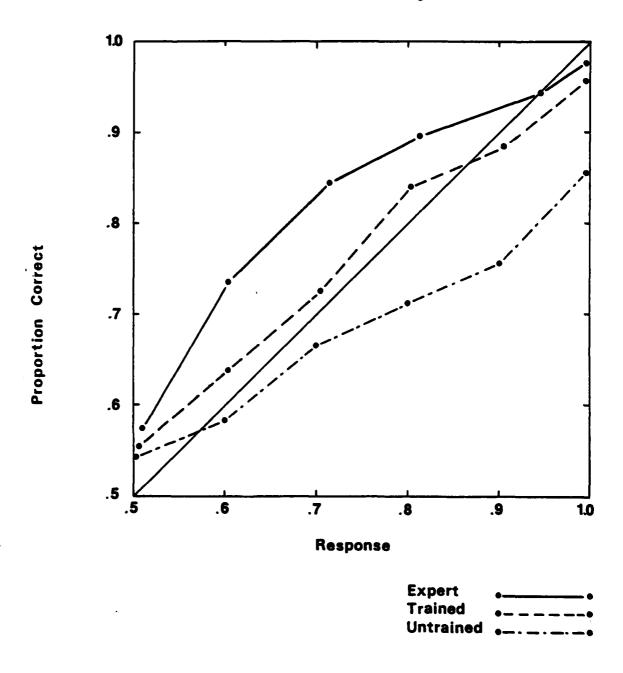


Figure 1. Calibration curves for the three groups of subjects. The responses of all subjects within each group were combined. In addition, all responses less than 1.0 were grouped into categories: .5 to .59, .6 to .69, ..., .9 to .99. The proportion correct in each category is here plotted against the mean response in each category.

Use of 1.0. The probabilistic response of 1.0 indicates complete certainty, and previous research (Fischhoff, Slovic & Lichtenstein, 1977) has shown that people use it too often when they are, in fact, wrong. The untrained subjects replicated this finding. They used 1.0 for 22.4% of their responses, of which only 85% were correct (Figure 1). The trained and expert groups were markedly superior, using 1.0 for 9.6% and 7.7% of their responses, respectively, and getting 96% and 97% of those correct. Two experts never used 1.0; one used it only for correct alternatives.

Difficulty

Our procedure for separating items into "easy" and "hard" tests proved quite successful. Over all 35 subjects, the percent correct for the easy items was 81.4; for the hard items it was 57.8. For all subjects but one, the percent correct on the easy items exceeded the percent correct on the hard items by at least 16 percentage points.

The effect of difficulty on calibration was striking for all subjects. On the hard items, subjects were notably overconfident (or at least much less underconfident; six of the eight experts were still slightly underconfident on the hard items). On the easy items, even 10 out of the 12 untrained subjects were underconfident. The group calibration curves for the hard and easy items are shown in Figure 2.

<u>Use of .5.</u> A response of .5 should represent a "pure guess," as likely to be wrong as right. But for easy items the percentage correct when our subjects responded .5 was substantially greater than 50% for all three groups (experts, 59.3%; trained subjects, 58.5%; and untrained subjects, 60.0%). Some experts' use of the response .5 on the easy items was

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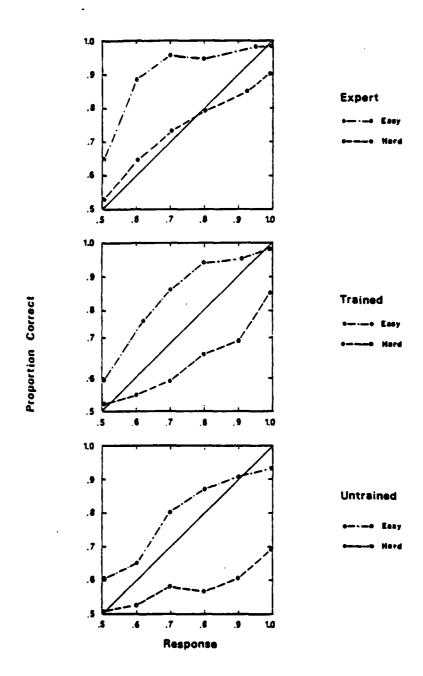


FIGURE 2. Calibration curves for the easy and hard tests, across all subjects within each group.

particularly discouraging: five of the experts responded .5 for 19% of the easy items and got 65% of them right, well above chance performance. The other three experts used artificial strategies for their .5 responses. One did not select an alternative when responding .5 (for data analyses, the computer alternated between a and b). Another always chose alternative a when responding .5, and the third adopted a constant-response strategy near the beginning of the task. Two of the trained group also made strategic choices of alternatives when responding .5. The others got 61% of their easy .5's right. It appears that even those well-schooled in the meaning of ".5" tend to choose the correct answer to easy questions they think they don't know.

Difficulty, overconfidence, and calibration. Consistent with previous research, the subjects in this study tended to be overconfident with hard items and underconfident with easy items. A necessary (but not sufficient) condition for good calibration is that the assessor be neither over- nor underconfident. The strong relationship between difficulty and overconfidence suggests that there is an "ideal" difficulty level for which an assessor will be neither over- nor underconfident and thus will be best calibrated. In Figure 3, overconfidence is plotted against percentage correct for each subject on the hard and easy tests. The straight line in each plot connects the group means. These data suggest that the untrained group might be best calibrated on a test on which they would get about 78% of the items correct. Lichtenstein and Fischhoff (1977) estimated this cross-over point at "approximately 80%" (p. 179) for a different group of untrained subjects. The trained subjects might do best on a test with 63% correct (close to the 68% they achieved in this test and the 67% they scored on the last round of their previous training),

and the experts would require an even more difficult test, 58% correct.

This reasoning suggests that, despite the apparently clear-cut results shown in Figure 1, we cannot unequivocally characterize an assessor or group as "better calibrated" than another without taking into account the relationship between difficulty and overconfidence. Perhaps the trained group weren't better; they were just lucky to receive a test with an overall difficulty level about the same as the difficulty of their training and thus close to their ideal.

Sensitivity to changes in difficulty. Assessors would perform better if they were more sensitive to item difficulty. Ideally, their response distributions would shift enough to make changes in mean response equal to changes in proportion correct. Completely insensitive assessors would maintain the same response distribution for all difficulty levels. Letting \Performance stand for mean assessed probability and P stand for proportion correct, and using subscripts h and e for the hard and easy tests, the ratio:

$$\frac{\Psi_e - \Psi_h}{P_e - P_h}$$

expresses the degree of sensitivity a subject shows to changes in difficulty. For ideal sensitivity, the index would be equal to 1.0. Values below 1.0 indicate undersensitivity; values above 1.0 indicate oversensitivity to changes in difficulty. Table 2 shows the means and ranges of this sensitivity ratio for the three groups of subjects. All subjects were undersensitive; however, here (at last!) we find a clear superiority of experts over the other two groups. Only two of the untrained subjects and three of the trained subjects were more sensitive

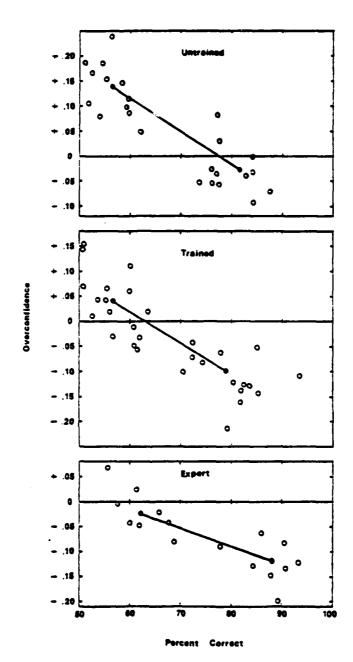


FIGURE 3. Overconfidence plotted against percentage correct for each subject on the hard (circles) and easy (triangles) tests. The solid symbols are group means.

to changes in difficulty than was the least sensitive expert. The trained subjects were not significantly better than the untrained group on this measure. 3

Discussion

At first glance, our probability experts appeared no better calibrated than the untrained group; both were inferior to the trained group.

Most of the untrained subjects were overconfident, whereas the experts were underconfident.

We will never know the calibration of our experts before they started studying the calibration of others. However, some archival data seem relevant. The first calibration data we ever collected used 19 employees of the Oregon Research Institute as subjects. Those subjects were similar to our present experts in that they were psychologists studying human judgment and their equally knowledgeable secretaries and research assistants. But they knew nothing about calibration. Their responses showed the now-familiar severe overconfidence (Lichtenstein et al., 1977, Figure 6). The underconfidence of the present experts seems to represent a change in behavior prompted by research findings. Apparently, they were determined not to be overconfident and, in their zeal, they over-corrected, becoming underconfident over a wide range of difficulty levels.

If this interpretation is correct, these results are moderately encouraging. People <u>can</u> learn from the experience of others. Readers of this article, having learned both of the general tendency to be overconfident and of the possibility of overcorrection, should therefore be able to produce well-calibrated responses.

Table 2
Sensitivity Ratio

	Group			
	Untrained	Trained	Experts	
Mean	.37	.30	.60	
Range	.04 to .68	.02 to .65	.45 to .73	

A more detailed examination of the data indicated that the labeling of one group of assessors as "better calibrated" than another is rendered moot by the systematic relationship between difficulty and overconfidence. This relationship is apparently mediated by an insensitivity to changes in difficulty. The experts were superior to both other groups in being more sensitive to changes in difficulty of the items, but the hard/easy effect was still substantial in the expert group.

The hard/easy effect can be viewed as a regression effect: If the correlation between the ease of item (defined by some objective criterion) and proportion correct is greater than the correlation between ease of item and mean response, as shown in Figure 4, then for easy items, one would expect to observe underconfidence ($P_e > \Psi_e$), whereas for the hard items, one would expect overconfidence ($\Psi_h > P_h$).

Some introspection suggests how hard it would be to be fully sensitive to test difficulty. Whether defined in terms of the proportion of people getting an item correct (as in Lichtenstein & Fischhoff, 1977) or by reference to some measure related to an item's content (as done here), item difficulty does not appear to be a piece of information above and beyond one's general feelings of uncertainty about which answer is correct. Intuitively, easy items are just those to which one is inclined to state a high probability, while hard items are those about which one is quite unsure. Sensitivity to difficulty might require a counter-intuitive, two-stage process, involving the assessment of both personal uncertainty and item difficulty ("I'm pretty sure I know the answer, but this seems like a hard item, so I'd better lower my confidence") before arriving at a probability assessment. Indeed,

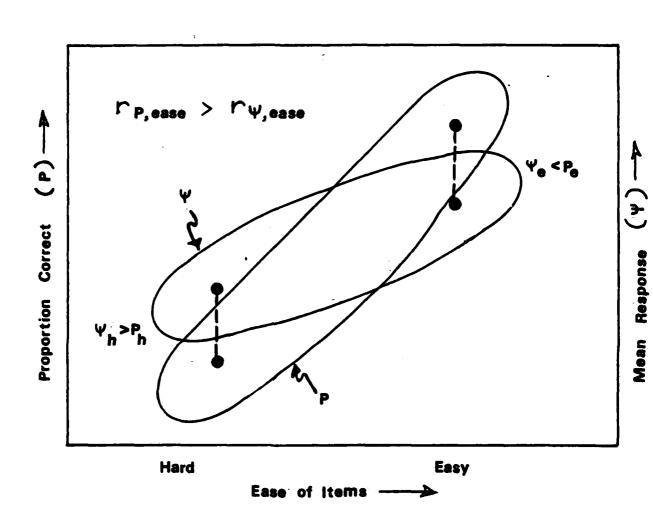


Figure 4. A schematic representation of how the hard/easy effect would result from a higher correlation between difficulty and percentage correct than between difficulty and mean response.

although both the present authors were above average (even among the experts) in sensitivity to difficulty, we did not consciously use such a two-stage process, and do not know how we did as well as we did.

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Footnotes

We acknowledge with thanks our discussions with Paul Slovic and Daniel Kahneman. This research was supported in part by the Advanced Research Projects Agency of the Department of Defense, monitored by the Office of Naval Research under Contract N00014-79-C-0029 (ARPA Order No. 3668) to Perceptronics, Inc., and in part from the Office of Naval Research under Contract N00014-80-C-0150 to Perceptronics, Inc. Requests for reprints may be addressed to Sarah Lichtenstein, Decision Research, 1201 Oak Street, Eugene, Oregon 97401.

- 1. Our deep thanks to Barbara Combs, Dennis Fryback, Barbara Goodman, Don MacGregor, Gordon Pitz, and David Seaver for serving as our expert subjects.
- 2. Because this measure is artifactually increased by the infrequent use of two-digit probabilities (e.g., .95), the data were grouped (.5-.59, .6-.69, ..., .9-.99, 1.0) for calculating the calibration index.
- 3. One-way ANOVA: F = 10.4; p = .0003. Trained vs. untrained, $\underline{t} = 1.20$, p > .2; trained vs. expert, $\underline{t} = 3.57$, p = .001; untrained vs. expert, $\underline{t} = 4.44$, p = .0001.
- 4. We are willing to analyze the results for the first 40 readers who write us to accept this challenge. You will have the advantage of knowing the approximate difficulty of the test.

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Admiralty Marine Technology
Establishment
Teddington, Middlesex TW11 OLN
ENGLAND

Director, Human Factors Wing Defense and Civil Institute of Environmental Medicine P. O. Box 2000 Downsview, Ontario M3M 3B9 CANADA

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Professor Douglas E. Hunter Defense Intelligence School Washington, D. C. 20374

Other Organizations

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Harvard University
Soldiers Field Road
Boston, Massachusetts 02163

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Research Institute
University of Southern California
Los Angeles, California 90007

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Department of Psychology
University of Oklahoma
455 West Lindsey
Norman, Oklahoma 73069

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Institute of Behavioral Science
University of Colorado
Room 201
Boulder, Colorado 80309

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Department of Engineering-Economic
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Stanford University
Stanford, California 94305

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Rice University
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